Season 3 Episode 1 – Nephrology First and AI Second
Guest: Navdeep Tangri, MD, PhD, FRCPC

Len Usvyat
Welcome to the Rena Research Institute, Frontiers in Kidney Medicine and Bio Intelligence, where we share knowledge and advances in kidney research with the world.

Joining me today for this episode is Dr. Navdeep Tangri, an attending physician and associate professor in the Division of Allergy of the University of Manitoba in Canada. Together, we'll discuss the development of the next generation of prediction models, helping transform chronic kidney disease care. Welcome, Nav.

Navdeep Tangri
Oh, thank you Len. It's always great to see you. I think this might mark ten years, since we sort of initially that, in real time, actually.

Len Usvyat
That's exactly right. No, that's absolutely true. And, since you bring that up, I actually wanted to chat with you a little bit about, some of the original work that you've started on, looking at, prediction of patients with their CKD transitions and how that all initiated. And what led you to that work. And I'd love to hear about this.

Navdeep Tangri
It's quite a long journey as all these things are. And I think that, there's surprises and bumps along the way. So, for me, the journey started, as a medical student, when I had just sort of decided that I wanted to study kidney diseases, be a nephrologist, and I was looking for a research project, basically shopping around because I had been told that it's good for your CV to have research.

So, I found a supervisor, who, at that time, this is now in 2001, was using neural networks to predict outcomes in kidney disease. And he gave me data from a dialysis registry, which was a really nice trials registry called a UK renal registry. And together we set out to predict, mortality in patients on peritoneal dialysis.

And we then set out to investigate whether there's any center effects in mortality. And we did it using neural nets. So, this is an interesting time because if I think back to 2001, 24 years ago, it would take a day to run the model, right?

Like we would set we would set up a set of parameters that it would let it run, it would take a day. So, you'd really have to think about not changing anything on the fly because it's going to take a day and then even the universe of reviewers and editors who would understand your work as you were submitting, it was really quite narrow.

And but I just learned a ton from that project. I mean, first thing I think I sort of learned was that, that these methods are wonderful, but not always the answer and not always superior. And two, that, predictions are really neat. Like, you know, you can actually you can do what we do in clinical medicine every day, which is try to predict future events and try to stop them, but quantify it like make it a science.

And so, I took a lot of learnings. From that and thought, let's try to quantify the decisions that that need like a precise probability in, in kidney disease. It just stayed very much in the kidney disease arena. And that led me to my fellowship at Tufts with Andy Levy, who I think if we think more generally about models, has developed the most widely used model in the world, which is the GFR estimating equation.

It's a linear regression model that takes a X and created it and predicts measured GFR. Right? I mean, it's a model. You don't think about that that as a predictive model, but it's a model. And so, I wanted to work with Andy. And you know, Andy and I kind of sat down and tried to define the project.

And we had looked at two projects potentially. One was again using better data sources to predict outcomes in patients with kidney failure on dialysis or to predict, time to kidney failure in people with chronic kidney disease. Thankfully, we chose the latter, and,

I had thought and Andy and I went back and forth on this a lot. I had really thought that the success of the GFR, the MDS, and then the CKD epi estimating equation, why it took over so rapidly from things like Cockcroft, Gault and, and, and so quickly was because it only required lab data. That was my kind of takeaway, that it was simple and it only required lab data. So, I insisted to Andy and Andy corroborate that story.

If you ever talk to anybody that it has to be lab data and it has to be only a handful of variables, otherwise no one will use it. So that's how we built K forests. We built them only with lab data and only with a handful of variables. I mean, subsequent to that, I could probably point to a number of models which we've developed, but some of them have non lab data.

But you can always tell from reading our work that that's like we really needed some other data. We always first tried to see can we just predict using lab data only because labs tend to be the source of truth. Standard labs tend to be done the same way across the world. And then the whole implementation, which is like the 95% of work that that needs to be done after a model's developed. It's just much easier, in my opinion, with labs, than it is with demographics or comorbid conditions or medications or so on. So that's a long-winded answer to how it all started.

Len Usvyat
I know that makes a lot of sense. And so, you've published so much about this kidney eGFR progression equations over the years. And I'd love to hear your story about it, because I know back in the day that were not usually used in systems like Epic or other EMR and of course now there are so widely accepted.

I'd love to hear your story of what led you to believe that I think publishing that information is actually the important piece of generating the evidence needed for the scientific community.

Navdeep Tangri
So, I think, again, a lot of lessons learned from always easier to do this, on the shoulders of giants. Right? So, I can point to lots of things in my career that I, that happened because the things I learned from Andy's experience. Right. So, I think we're through one very big cycle of risk equations being used, and we're about to kick off, like, sort of a super cycle thanks to the KDIGO guidelines, the in 2024 that just came out and recommended one way to use risk prediction equations.

So, one of the things I learned from Andy was guidelines are really important. So, guidelines are a lot of work physician. It's purely volunteer. But I think if you're a physician or a physician scientist, if somebody asks you to participate on a guideline, say yes. Because in many, many parts of the world, payers, providers, policymakers, lab medicine, people follow guidelines.

They will do things. The guideline sets. So, if you get a chance to be a part of a guideline, always do it. I think the other thing was, you know, how do you make things automatic? How do you automate things and make it as easy for physicians to use? Right. Again, Cockcroft called requires a wait. Wait is typically sparsely recorded.

EHR is not available in the lab. And obviously there's other differences between Cockcroft called and MD. Really. You know, the big success of everybody, just the lab, right? Only the lab needs to know to report it. So that's what we did with the Curies. And then, on day one, and this was like a very unique thing at the time, in 2011, when we published the original models on day one of the publication, simultaneously, we had an inclusion in a smartphone application.

So, QCs calculate kind of implemented it on day one alongside online publication. And that was very new. It was I think we were the first at that to do it at that time. Which is great that now everybody sort of does it. It's expected that you create a shiny app or something, even when you sort of publish a model.

And then it became sort of a journey where initially it was sort of me offering labs and EMR records and health systems. Anyhow, I had to, but we had developed sort of a playbook on how to implement, and we would send this out everywhere. Anyone who asked and now it's thankfully flipped the other way around. Now we constantly get requests for, hey, we want to implement this.

What's the playbook like? Do you have you know, what thresholds should we use? How should we do it. And so, we sent that out and I think, this eye on dissemination is really, really important to, to get things used rather than just publishing and, and ending the cycle there.

Len Usvyat
Yeah. No, I think it makes now I think it makes definitely makes a lot of sense. You mentioned guidelines and the importance of guidelines. And do you think with others, particularly with large language models, do you think these teams will play a bigger role in actually creating guidelines, as well in the future.

Navdeep Tangri
That's a really neat question. I think one of the things that consistently comes up as a criticism of guidelines is maybe shortly a little better than textbooks, but guidelines are also often considered out of date by the time they're published because of the lengthy review process and so on. So how could we accelerate? First, I think, alarms have a nice role to play in evidence review.

Right. So abstract screening, synthesizing evidence, doing systematic review and meta analyzes faster, which are of course, the backbone of a guideline. Right. Like the evidence review, of course. So, if you could accelerate that evidence review process you can help the guideline readers make better decisions. Then I think the authors of the guideline can take all that evidence, take those tables, take those figures, write some content for the guideline or let's say call it the KDIGO guideline. In our case since we're talking about kidney disease.

But then how do you disseminate. So can you give that guideline to an LLM and ask it to generate a patient summary. Can you ask it to generate language translations into different languages? Can you ask it to generate infographics based on the guideline, to more rapidly disseminate the information? So, I think there are these key forks, which LLMs can be quite helpful in sort of accelerating the adoption of evidence, to practice.

Len Usvyat
No, I think makes sense. I know you validated many of these equations. Of course, on the KFRE equations were validated in different, diverse populations globally. And I'd

love to hear your perspective on using AI globally, validating this information globally, because I certainly think it's important. I'd love to hear your thoughts.

Navdeep Tangri
Again, this would be a great part where we should compare and contrast findings, because I think you come from, organization that's global as well. So, you probably deal with the same issue is about is something that we develop here applicable in another country, another region, a different patient population. It's probably a bit of a generalization, but one could say a fair generalization that a simple regression model with limited number of interactions is less, you know, it's less likely to be overfitted or is more likely to generalize in an independent sample than a more complex model, which has multiple interactions, multiple non-linearities, and going all the way to the spectrum of like, you know, a deep learning model on a narrow data set. Right. So maybe it's fair to say that external validation is important for all models, but perhaps the most important for models that are developed using AI or machine learning methods. One of the things that we got over very quickly, that I would urge the listeners on this podcast to get over very quickly, is this fear of data sharing or models sharing, right?

Like, fear paralyzes research, fear paralyzes innovation. And often it's unnecessary. I'll pull out some sort of pie in the sky examples. Right. So, we're trying to do this project right now. And this is not specifically related to machine learning validation. But we're trying to do this project where we're trying to look at the provincial lab data and find people who are high risk for kidney disease progression, who've never seen a nephrologist.

And we call the project Safety Net. So, we sent them a mail out. We break the privacy ceiling, we send them a mail out saying, hey, you know, you have high risk kidney disease. We're offering you a consult. So, we had a really difficult time with ethics boards and other privacy commissioner saying, oh, you know, you're breaking someone's privacy by notifying them kind of sort of out of the blue, even though the notification is coming from the Department of Health in a public health care system.

And I think, those people, they're not interviewing the patients and asking them necessarily, hey, if you had high risk kidney disease and someone knew about it, would you want to be notified? So, I think this kind of these privacy fears, while justified in like a global context sometimes can be overblown and, and maybe in a stretch in a tangent, these privacy and fears keep validation from happening and everyone says, oh my data can't leave, my data can't leave. Well, your data doesn't need to leave. Right?

Len Usvyat
Right.

Navdeep Tangri
We have become so good at sending code, sending model objects and writing scripts so that the precise output comes back and tables and figures, and you can then meta analyze it. I mean the entire CKD prognosis consortium. So, I'll shout out to Joe Corish and Morgan Grahams here who have done incredible work. The whole thing exists based on this federated learning concept that you don't need to share data, you just need to share output.

And so, you can get very comfortable validating your findings. And you should know that even if you think your model is the best, no one's going to use it in a far-out place with a very different health system without local validation. So, expect it, encourage it, and make it feasible. Right? Because rather than saying, hey, believe my data, it's all good.

So, tell me you know, how did you let's say let's call it anemia management, right? Let's say you develop an anemia management model using a US population. What are your steps before you implement it in Europe? In APAC and Latin America. So how do you do it at Fresenius?

Len Usvyat
This is a very common problem for us, as you said. I mean, just because we do have clinics. Fresenius Medical Care has clinics all over the world, so we very often may create a model that is created in one region, but we want to try to use in another region. I think there are things that are purely biologic, which I think maybe a little bit easier to say, well, that could be used, globally. But then there are other things like practice patterns. So, for example, hospitalization model that may be developed on the US population. You really need to adjust that to, each individual country, because we all know that how people go to the hospital, how frequently they go, what the payment different system or what the different payment systems are in different regions.

All of that may vary quite a bit. So, we will always readjust the model for things like this that is very specific to whatever the geography that we try to use the model. And I think one of the things we always try to do, and I think I was actually going to, also ask you this question, but I think we often learn something from adjusting the model to another geography that then we'll say, well, you know what?

We should have considered this here as well, because we just didn't think about this. And I was just going to ask you this question. Can you think of examples for these, KFRE equations where you said, you know what this was developed from this population, but actually, see, now by applying it to a different population, I see that maybe I should be making some adjustments and maybe incorporating additional variables that I haven't traditionally thought about by using it somewhere else.

Navdeep Tangri
I think we're both agreeing that adjustment and a local specification. So, like a locally calibrated version of model X is the best than model X in its original form. Now sometimes you don't need that local calibration, but it's a bit of a flip, right, for researchers. And I think that we tend to think that, hey, I have developed this great thing.

It works everywhere. And maybe some people see local calibration as almost a failure of the model to generalize. I would be in your camp, but I would argue that it's a success that you've now given that country the best, like in our case, the best KFRE for the UK.

So, for us, for example, Rupert Major in Leicester did a UK specific KFRE and then he developed UK specific thresholds for referral because based on UK primer, because UK has got good NHS like primary care data. So, he had the tools to develop it and different variables. I don't have enough experience to say which different variables could have been added and some may be very valuable in different countries.

But local calibration has been invaluable for KFRE, because there's nothing wrong with a UK KFRE, an Indian KFRE, a Chinese KFRE. That's okay. Right. That's actually good. That's working as intended I suppose.

Len Usvyat
I agree and I know we touched upon this a little bit, but I want to dive into it a little bit deeper with the whole idea that now that many of these equations are incorporated into different EMRs, what do you think has led to that success? Obviously, the equation, obviously it's you and your collaborations, but I also think publishing is a big deal. And so maybe you can talk about the publishing aspect of it.

Navdeep Tangri
I think publishing is really important. I think we live in a constant hype cycle, and especially again, not most true again, about AI, unfortunately, these days that regression models, I'm sure, every day on LinkedIn, you and I see lots of white papers. Anybody could make a white paper.

Right. Like, I think that what distinguishes us from the white papers of the world is that you have gone through peer review and. Yes, there are some limitations to peer review, but certainly the standard is much, much higher orders of magnitude higher than a white paper. I also think that the barrier to publication is not insurmountable.

Right. So, you know, RRI is Renal Research Institute, which is an arm of, a commercial entity. But you publish your work, right? So, I think hiding behind a commercial entity is saying, oh, sorry, we can't publish our work because it's proprietary and commercial. It's

simply not true. Right. And maybe this is something where, I firmly believe that it's essential.

It's a mark. And it distinguishes the best from the rest. But maybe the real answer is like the listeners, the consumers of this technology, right? The consumers of the model, the consumers of the generative AI application should demand it. Don't settle for the white paper, because every white paper out there in dialysis or kidney disease will quote you the magical 20 to 30% reduction in events and 20 to 30% reduction in costs.

The white papers don't give you an opportunity to look under the hood. Whereas a paper and definitely the supplement of the paper gives you a good look under the hood and you can decide.

Len Usvyat
And I think, as you said, we're very fortunate having access to a very large, at least in the dialysis on the ESKD side to a very large database. And I think it's truly our obligation to publish, and it's truly our obligation to collaborate with a scientific community. Which brings me to my next question. As you know, both you and I are, you are leading this ASN, AI community group that we're both part of, and I certainly found it an extraordinary experience being part of it.

And one of the things that you once said that really stuck in my head is this idea of nephrology first, AI second, which, I think makes sense, of course, to me. And I think you just phrase that probably better than I ever heard it phrased in the past. Maybe you can talk about that a little bit, because I do think this is very important to all of us, in particular clinicians.

Navdeep Tangri
Thank you. That's very kind of you. For me, it's also been an equally fulfilling experience to be a part of this group. And I also learned so much from the incredible members that we have. The way I thought of it was that what sets us apart is that we, as physician scientists is that we are able to try and solve a clinical problem with a toolbox.

And that's what I mean by nephrology first, AI second, AI is the toolbox. Nephrology is the clinical problem. I think if we flip the switch and we start to go 180 degrees or whatever however you want to call it, if we go with the tools first and look for a problem that will lead us astray.

I think it will lead us to inventing problems. It will lead us to ignore, concerns about privacy and overreach, and it will diminish our role if we look for the toolbox first. And this is a bit of m rant side of it is that I think tech companies, per se, you know, certainly have a role to play in the ecosystem.

Big tech is a part of all of our lives, right? Like Microsoft, Amazon, Google. And if you look at the players, they're dominating this space. Yes, there's a lot of small vendors and, you know, startups that are in this space. But it's still very much largely dominated by the big companies, right. That Amazon has Q.

And there's Meta has its own Google and Microsoft, OpenAI. When you look at the kind of, white papers that come out of some of these organizations, sometimes they'll publish their work, sometimes it's preprints, sometimes it's white papers. You look at some of them that come out, maybe they don't intend it that way. But there certainly is an undertone, at least in how it's picked up in the lay media of a sense that it's going to replace physicians, or it's better at making diagnosis.

The headlines always read this way. Maybe they don't mean it. When you read the preprint, it says, you know, it has a lot of caveats, but that's not how the headlines come out. Right? I think of countless, countless LinkedIn or other press releases I've read over the last year where it's been like New England Journal of Medicine, challenging cases, AI does better than physician or these diagnostic cases.

And I think to myself, is that really reflective of how a physician patient relationship works. When I go see a patient, do I receive, a multi-page, comprehensive history with all the investigations well laid out and I'm asked to make a diagnosis? Actually, it's not like that at all, right? Like it's, so much of what we do is in gathering information and those cases that you're asking the AI to solve it.

Often, you're comparing to a physician who has no access to the internet, a completely unfair comparison. Today's physician is armed in technology, armed with evidence and ready to use it. And the comparisons are not entirely fair. And it doesn't mimic workflow like the everyday practice is not New England Journal of Medicine challenging cases. So, for this reason, I'm not ready for big tech to tell me that they have the answers to all my problems. I'm ready for us, the audience here and the two of us to identify the problems and use a variety of tools, whichever is the best tool necessary to solve the problem.

Len Usvyat
And I would definitely say some of these phrases often get stuck in my head, but I think one of the ones that I always remember is the health care is the graveyard for some of these tech startup companies. And I do very much think one of the reasons is because physicians and clinicians are not often part of the development of what actually happens, and what are these algorithms that we're developing.

And to me, it is so important to have the combination of the clinician also using the technology. I mean, what you've done, you know, as you said 20 years ago, whenever you started working on the first models, it's because you had clinical understanding and

you were able to use the technology. And I certainly do think even if we look at our own data, before our first algorithms were put into place, clinicians will always write about anemia and prescribing ESA and EPO.

And how much EPO should the patients get? Over time that has changed, because we now have a lot more algorithms that make that life of the clinician easier, so that they can focus on more complicated cases, which is, of course, why we want doctors to be here. And they will always be here. And as you said, I think AI is a tool in the toolkit. I think we both would very much agree on that topic.

Navdeep Tangri
Anemia is a wonderful example of where I think it can be really useful where the marriage really works. It's upskilling, you know, can we upskill, the nephrologist, by freeing up time for anemia management, maybe dry weight adjustment, maybe, you know, vitamin D or phosphate bind to precision management and upskill them for the more complex, you know, dialysis issues like, how do I get this patient waitlisted for transplant?

And can we use, prediction models and accompanying decision support to upskill primary care doctors to be like nephrologists or nurse practitioners or advanced practice providers to be like nephrologist like? So, these are these are some of the ways I think it's like a perfect use case. You take specialist domain input, you use an LLM, you help people interpret something that they don't see every day.

Right? Because I think, the hardest job in medicine is being primary care provider. You're expected to know everything and that everything is just growing and growing and growing. Right? So, if you can have some tools to upskill you before you need to reach for the specialist, that's wonderful for health systems because that means that specialists can be also upskilled, because they'll be looking after the more complex cases.

And, that patients stay with their physician, which I think longitudinal relationships are wonderful. That's one of the main reasons we go into non-surgical medicine is because we want longitudinal relationships.

Len Usvyat
I think that definitely makes sense. What are some, Nav what are some of them, other than, of course, the GFR progression equations. What are some other examples that you think you personally worked on of that work's been done particularly using AI and technology these days that have really seemed to be changing the way the therapy is being delivered or treatment is being delivered.

Navdeep Tangri
Everything starts in prediction and machine learning from images and deep learning, right? Like deep learning is kind of the beginning. It's been going on for a while. It's now a sort of in the very rapid upswing. So, in radiology there's so many of these tools.

Right. And I think closely following radiology is cardiology. You see multiple approvals for echo based or ECG based algorithms that are now able to detect structural abnormalities just based on patterns of ECGs. You know, detecting hyperkalemia, detecting amyloid cardiomyopathy. And anything like EEG, I think is a natural fit spirometry I saw recently another publication, you know, kind of learning how to interpret astrometry.

Our work is in lab data. It's sort of this idea, that we are just going beyond the deep learning imaging now. And I think some of these we're going to see really flow out into practice in the next few years. Now there's a lag, right. Like I think you know this, a few years, you develop a model, then some of these have to have a regulatory path.

So, then there's a regulatory path, then there's a reimbursement path. Then there's adoption. Even after all that. You have to do regulatory reimbursement; you still have to get adopted. You have to get people to use it. So, but the attitudes are changing. I mean, these days when we talk to ASN members or even just in public, people want to, adopt, right?

They say, you know, make it work for me. I'm willing, I'm willing. You have willing listeners because people don't want to be left behind. So, I think that’s a good time if you're developing tools in this space. It's a good time.

Len Usvyat
I definitely agree with you. I guess you also indirectly bring up a little bit on the kind of the generational issue, which of course exists. I think we can all acknowledge this. I understand that it may be harder to adopt certain technology for people, you know, maybe a little bit older or younger there, maybe a little bit of a difference. I don't know how much what your thoughts are on the topic, but I do expect personally that there will be more uptake of these technologies as time goes on certainly.

Navdeep Tangri
I think so. I think so. And I think that, probably the best thing that, people of my generation could do is stay flexible, right? Because, you know, I think we don't always know best. And it's very generational to think that your generation knows best and the generation before it, the, you know, the younger generation doesn't know what they're talking about.

So, I think that, we should stay open, open, but critical. Critically evaluate, but stay open because, there's lots of good things in there, that we can learn now. It'll be interesting. We're still, I think, early days in the, the daily interactions. Right. Like, how many interactions will we start to have with, somewhere we moved from real people in our neighborhood to real people in our country to real people in a call center somewhere halfway around the world. And I think we're about to move to virtual people in a virtual call center. So, for a lot of our day-to-day interactions. Right.

Len Usvyat
Very possible, very possible. Yeah. I mean, I don't know if you've done it, Nav if you guys have done a lot of this work, but certainly some of these rags and, you know, things you could do with large language models where you can, you know, put a lot of your source material and create much more of these chat bot like interfaces to your documents.

Navdeep Tangri
Yeah. I think that that's like a source of truth really helps. Right. So, then you could restrict and I'm here from Winnipeg, Canada and one of the leading kinds of customer service provider call center provider companies is based here in our city. And this is what they do.

They, they take like the manuals and the entire guidebooks for a particular consumer. And they use large language models that they're, you know, they use Rag to really provide a customer service chatbot. Recently I saw that our, local police department is doing the trial on, you know, for 911 calls for a chat bot for some sort of triage system.

So, I think, again, early days, probably somewhere in the 2020s or early 30s, a lot of our conversations are going to be, certainly with AI agents and chat bots rather than with real people. And that'll create a societal should. Of course. Now we're really getting, off course, here, but, you know, self-driving is also happening.

So, there are these probably generational things happening as we speak. And, and we'll be learning the impact of it together. But you have to stay open. So go ride in that Waymo and talk to the chat bot and do the thing.

Len Usvyat
Nav, can you talk a little bit about how AI and machine learning, what role can it play in genetics and analyzing genomes and other areas? Not just purely prediction models, which of course, is as you said, is the kind of the first step.

Navdeep Tangri
Thank you. It's an exciting question. Some of my most fulfilling and best things I've done in my career have been as part of drug development programs. And some of it was pre-

AI use and just learning about how regulation works at FDA and how payer reimbursement works. And I did some of that work with TriZetto which was a biotech based in San Francisco, and this opportunity came where, colleague and friend Ben Hippen asked me to see if I could help this company.

So, this is a nice story because it marries some of my sort of regulatory and reimbursement expertise with the idea of using AI to harness insights from a very large and well curated genomics database.

Because when you look at genetic data for people with chronic kidney disease, it's completely dominated by people with EGFR 45 to 60. And those people, they are a mixed bag. There are people with borderline creatinine. There are people with a lot of muscle mass, people who ate a high protein meal the day before, and there are people with real kidney disease in there. So, the signal to noise ratio is very high in eGFR 45 to 60 definition of CKD. But with kidney failure, it's such a dramatic striking event that it's not a very common event that when you take and the approach, which is, what is my signal to noise ratio in someone who has kidney failure versus someone who's kidneys are healthy, then it's really amplified or a lot more signal to noise.

And you combine that with computational tools and AI, and you'll get some signals. So, I can help, I have an opportunity to help a little bit validate some of those signals and say, this is probably a true positive versus a false positive. And then you bring in like drug development, right? Which is just a regulatory science.

It's a completely non-AI thing, which hopefully puts those things together. We have a team and I'm far from the only expert on the team. Will bring therapies that will be meaningful for kidney disease.

Len Usvyat
And of course, I believe you also have access to especially with ESKD, and have access to extraordinary phenotypical data, which I think is quite rare in any other segment of healthcare to have so much information on the patients.

Navdeep Tangri
Very, very unique data set and just the right time, the right moment in time, where you have this unique data and you can analyze it to get the right insights.

Len Usvyat
in conclusion, I'd love to hear your thoughts. As an expert in the field, where do you think things are going? And maybe not in 50 years, but you know, in the next five years, in the next ten years, what do you think we'll see more proliferation of, in terms of tools and technology and AI tools for patients with kidney disease.

Navdeep Tangri
So, I think there will certainly be more tools. It doesn't take a genius to figure that out. I think we're going to see more tools, but I hope with that also comes higher expectations. I think the consumer is going to drive this, the medical consumer in this case, which is kidney doctors and nurses and care providers should demand excellence, demand publication, and demand to understand what's driving the prediction and engine.

At the same time, I think there's this willingness today to accept AI tools as useful decision aids in our data life. Like, if you use ChatGPT to plan your trip, then it's okay to use, approved like FDA cleared model to help with your clinical decision making. Believe me, that's held to a much higher standard than planning your trip, right?

So, I hope that that carries through. I hope that people take that same way that they've embraced these technologies for their day-to-day mundane tasks and say, hey, like, this tool could also help me in my workflow. And where I hope all of this happens is it leads to upskilling over the next few years. That all of us across the entire spectrum, from APP and primary care all the way out to nephrologists, and now we have like Subspecialists, all become better.

We all become faster. We become better. We're able to look after our patients more. And I think that's feasible. I think that's feasible, and not just in the next 50 years. That's feasible in the next 5 to 10 years. So, I'm quite optimistic about that.

Len Usvyat
I think we're on the same page on many of these topics. I think what has happened in the past few years, and particularly now, I think we're really seeing this evolution, and I almost feel like the momentum is building where I do think we'll see a lot of a lot more changes in the next few years, particularly in this field. I think it's been trickling slowly one by one. And I do think our work, certainly on the ASN AI Committee, has been very helpful in bringing some of these thought leaders together. So, it's been wonderful. Nav, thank you so much for your insight into the discussion and obviously for really being so instrumental in many ways, I think, for starting many of these prediction algorithms, certainly on the CKD progression. So, I've always admired it from the very beginning. So truly, thank you for the discussion today.

Navdeep Tangri
Thank you for having me. I thank you for the great conversation.

Len Usvyat
And thank you to our listeners for joining the Renal Research Institute for this episode of Frontiers in Kidney Medicine and Biointelligence. We invite you to connect with us on our social media channels and stay tuned for future episodes as we continue sharing insights and advancements in kidney research.